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Title: Bi₂Te₃ Wafers Inspection Update

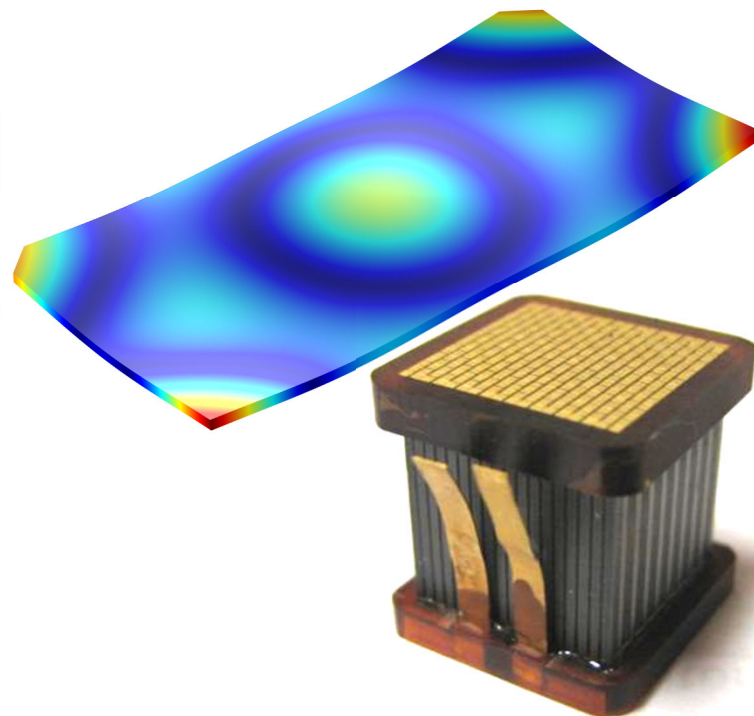
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Progress update: October 11, 2018

Bi₂Te₃ Wafers Inspection Update


John Greenhall, Cristian Pantea, Eric Davis, Craig Chavez, Dipen Sinha, Alan Graham, Scott Grutzik, Joseph Dumont, Pat Reardon

Bi₂Te₃ Wafers Inspection Update

Primary objective

- **Develop a fast and efficient technique to detect cracked wafers via combination of machine learning, optics, and ultrasound**

Bottom line

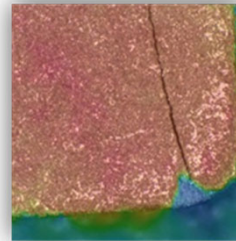
- **Low measurement time (<3 min/wafer)**
 - **Technique detects 100% of cracked wafers, and most wafers with other damage types**
- 

Presentation outline

I. Wafer defects and critical flaw size analysis

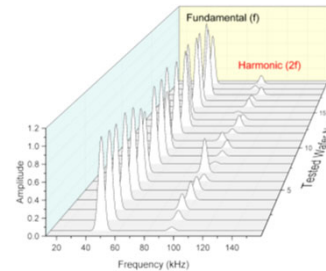
$$a_c = \frac{1}{\pi} \left(\frac{K_{Ic}}{Y\sigma} \right)^2$$

II. Optical measurements



III. Acoustic measurements

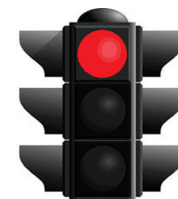
1. Acoustic resonance of wafers
2. Acoustic nonlinearities



IV. Statistical trial of production wafers

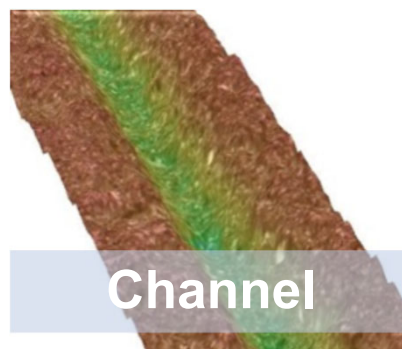
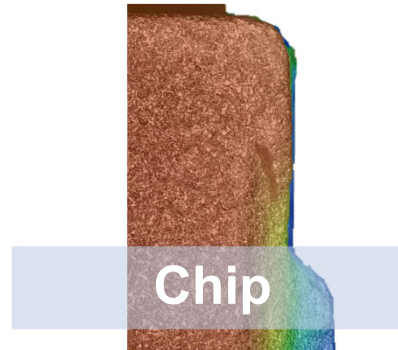
V. Damage classification

VI. What's the future?



Wafer Defect types

A number of different defect types have been identified:

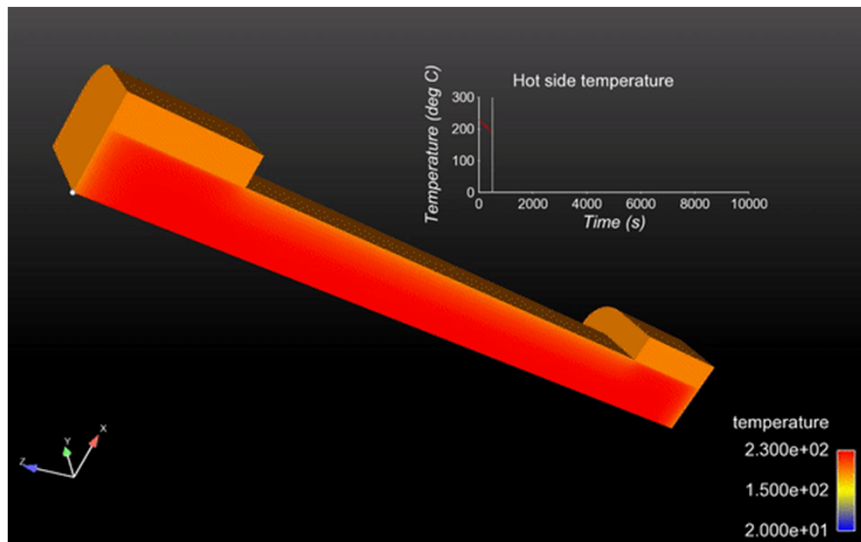


Primary objective

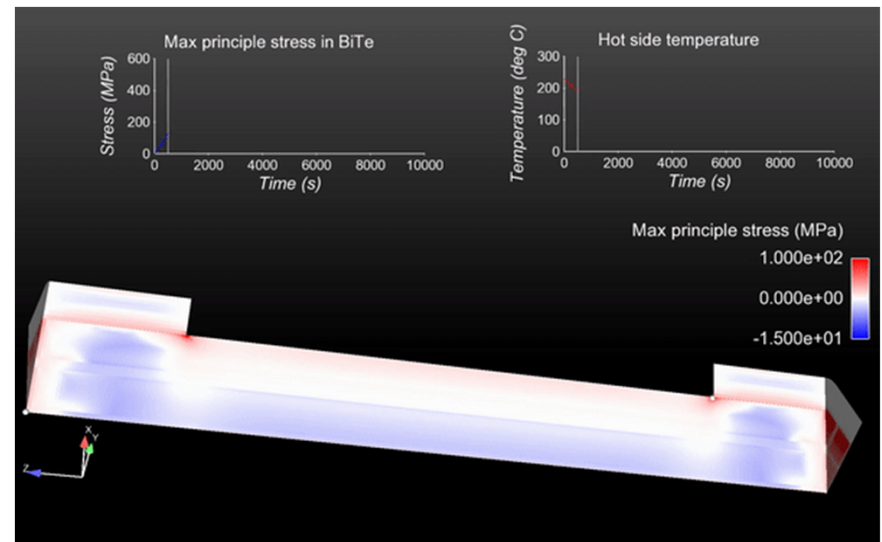
Can we identify flaws that could grow to be cracks during processing or service?

3D Models Determine Maximum Tensile Stress During Cool Down After TEPOX Epoxy Curing

Temperature



Principal Stress



Current best estimates of the maximum principal stress, $\sigma_c \approx 50 \text{ MPa}$

Conservative estimate of Bi_2Te_3 wafer critical flaw size

Critical defect depth:

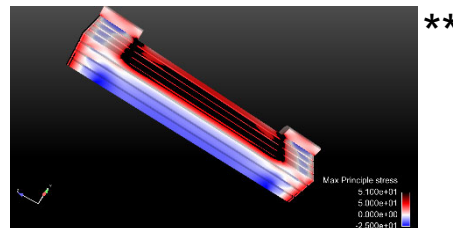
$$a_c = \frac{1}{\pi} \left(\frac{K_{Ic}}{Y \sigma_c} \right)^2$$

$$a_c > 110 \mu m$$



Stress intensity factor:*

$$0.66 < K_{Ic} < 0.82 \text{ MPa}\sqrt{m}^*$$



Geometry correction factor:

$$Y = \frac{2}{\pi} (1.211) \approx 0.8$$

$$a_c \leq 110 \mu m$$



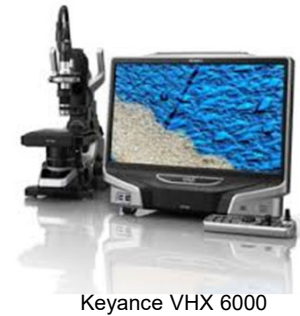
Maximum principal stress:

$$\sigma_c \approx 50 \text{ MPa}$$

* Range for N and P Bi_2Te_3 - W.Y. Lu, SNL Memo on "Fracture Toughness of Ultra+ Materials", August 7, 2017

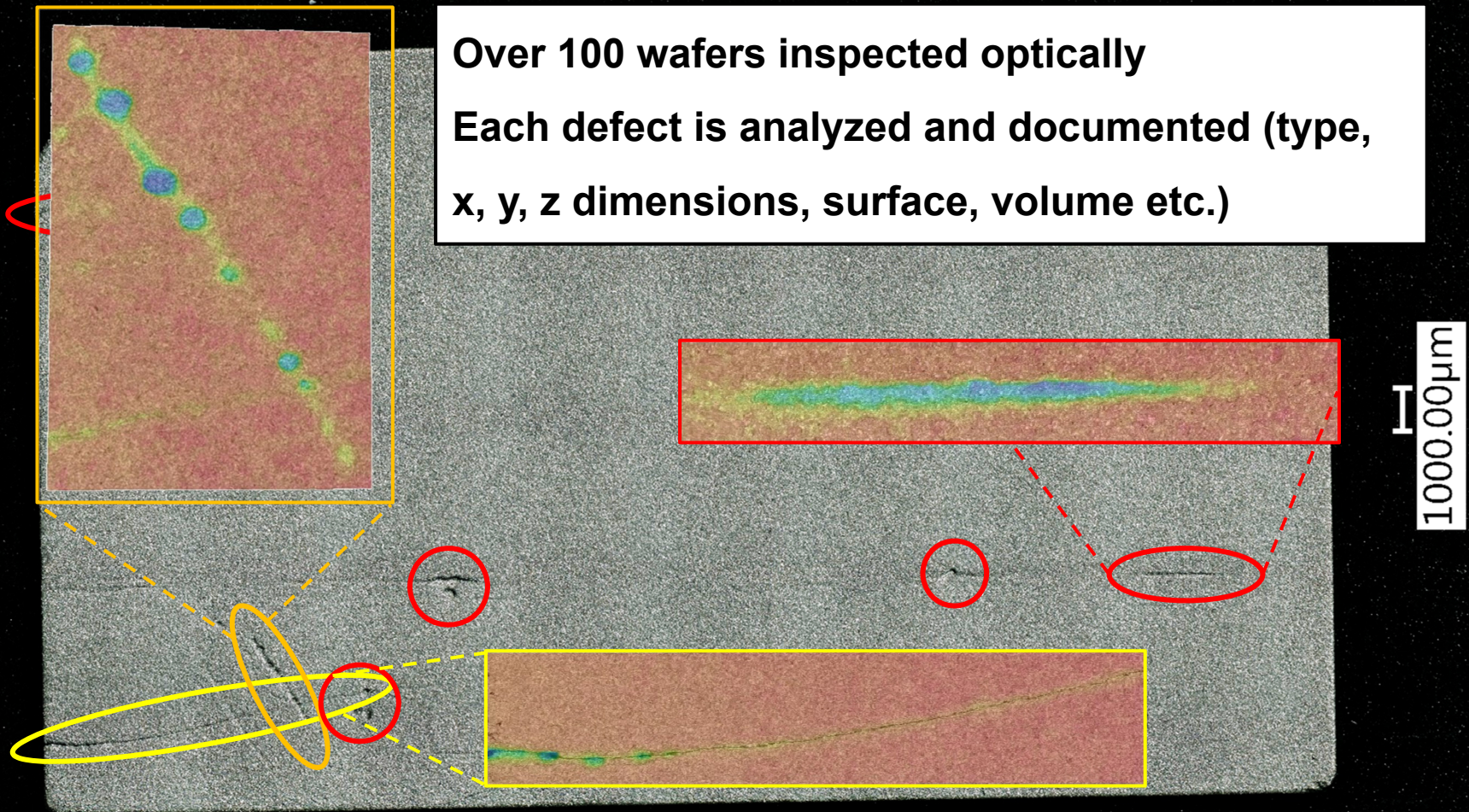
** Scott Grutzik (2017) Sandia National Laboratories

Optical measurement of wafer defects



Keyence VHX 6000

Over 100 wafers inspected optically
Each defect is analyzed and documented (type, x, y, z dimensions, surface, volume etc.)



Summary of optical measurements

Microscopy allows us to gather information on individual wafers

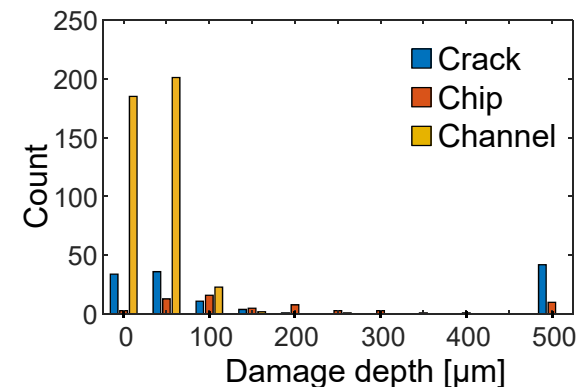
The constitution of a library of defects is indispensable to better understand the materials characteristics. We are attempting to correlate it to the acoustics data.

***Over 100 wafers inspected optically
Over 400 individual defects reported***

Cracks: 128

Chips: 63

Channels: 442



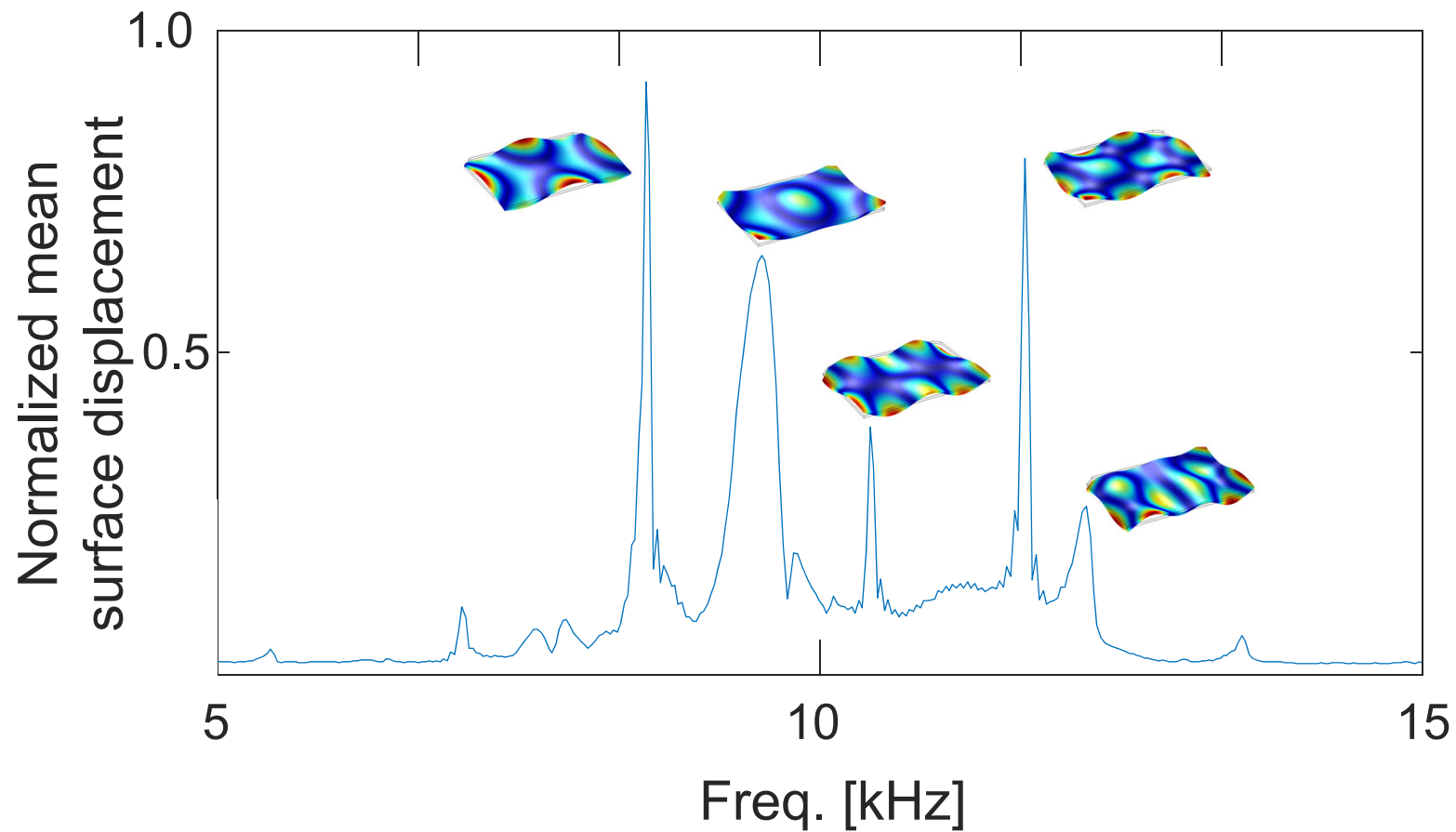
Acoustic crack detection in Bi_2Te_3 wafers

Goal: Detect wafers with cracks $> 110 \mu\text{m}$

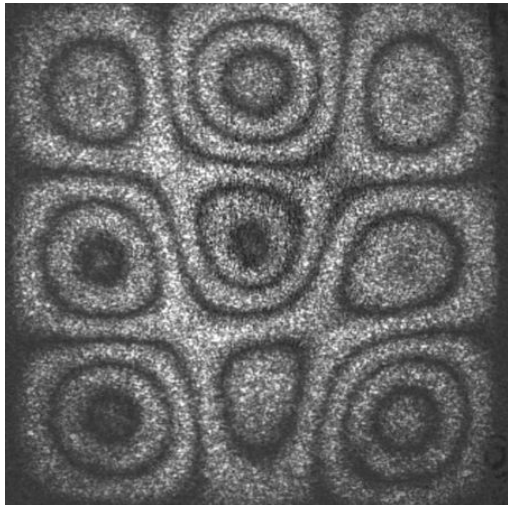
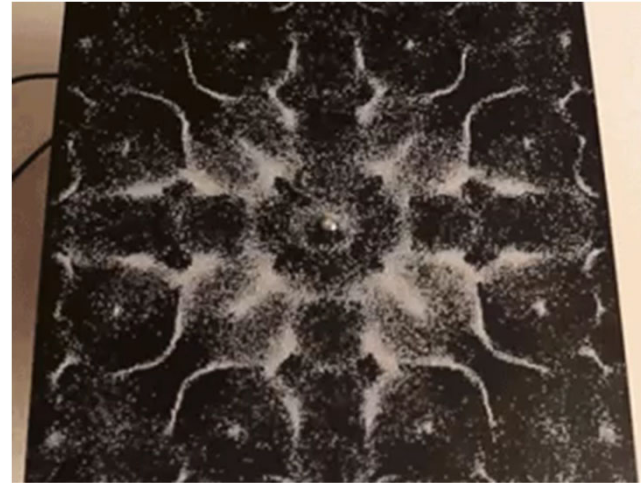
Secondary goal: Detect wafers with channels $> 110 \mu\text{m}$

Acoustic Resonance Spectroscopy (ARS)

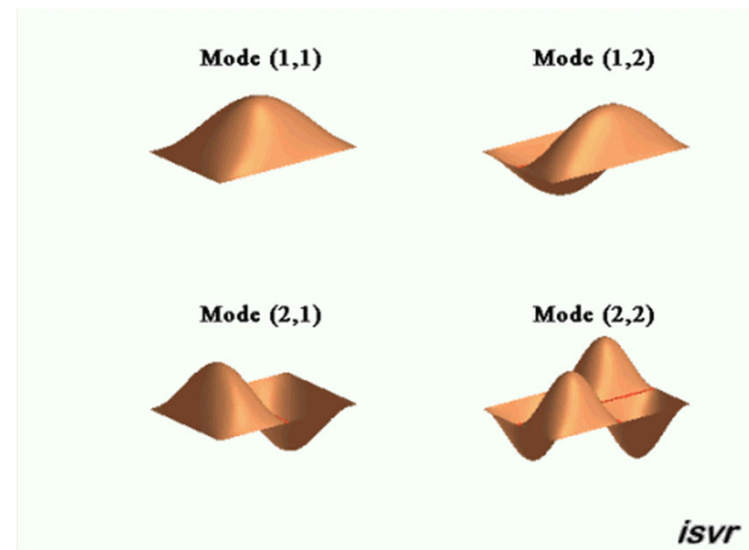
Wafer vibrational modes result in a peak in the mean surface displacement



Chladni Vibration Patterns of a Plate



Laser Vibrometer Patterns

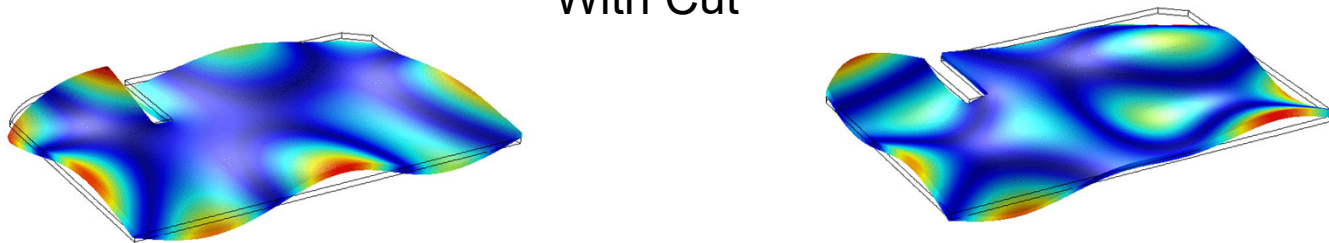


Vibration Characteristics Comparison

Defect Free

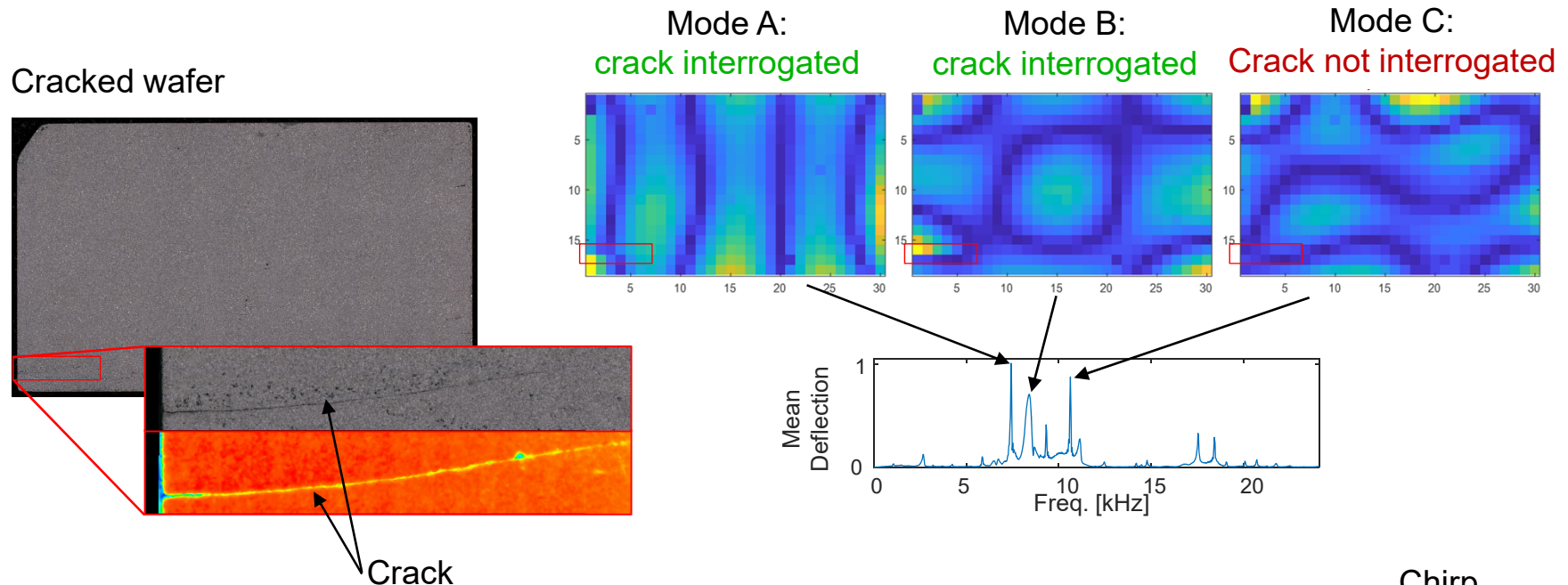


With Cut



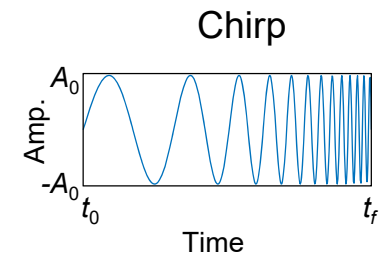
Effect of Crack Location

Crack excitation amplified when crack coincides with resonant mode maxima



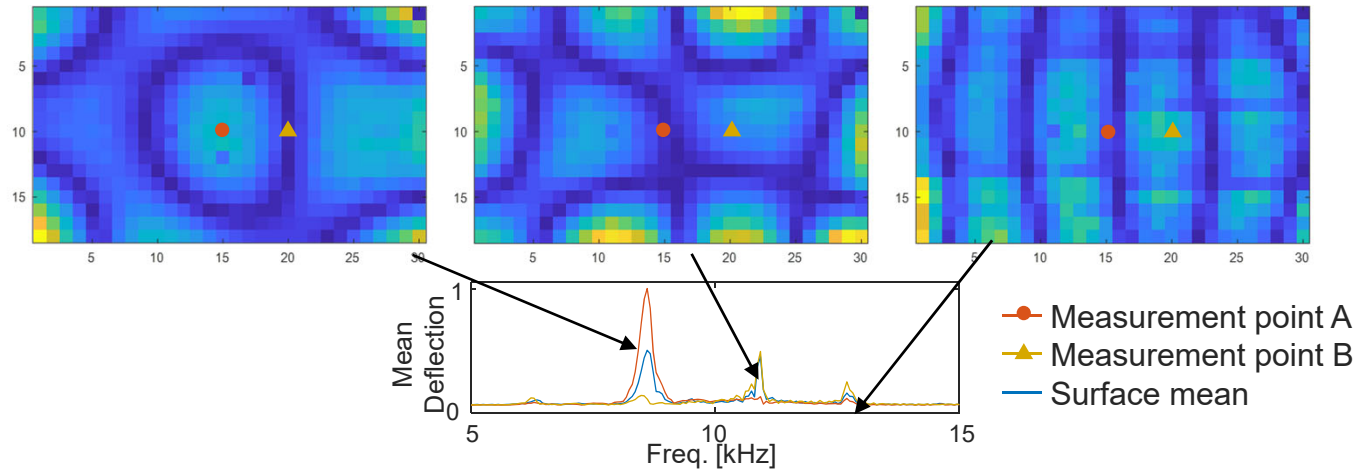
We must excite multiple modes to ensure crack interrogation

We select a chirp from 8 kHz to 12 kHz to excite ~3 wafer modes

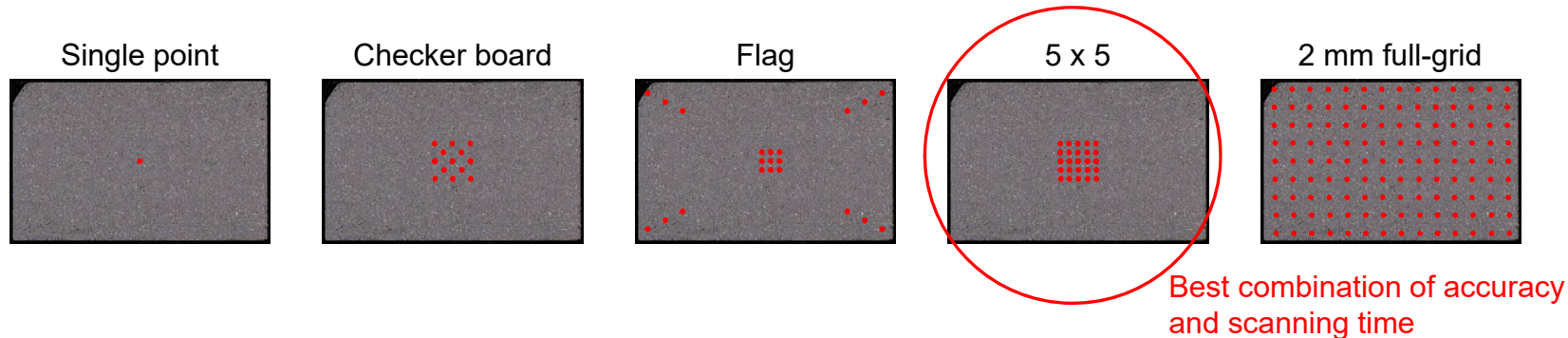


Effect of Measurement Location

Measured signal dependent on measurement location

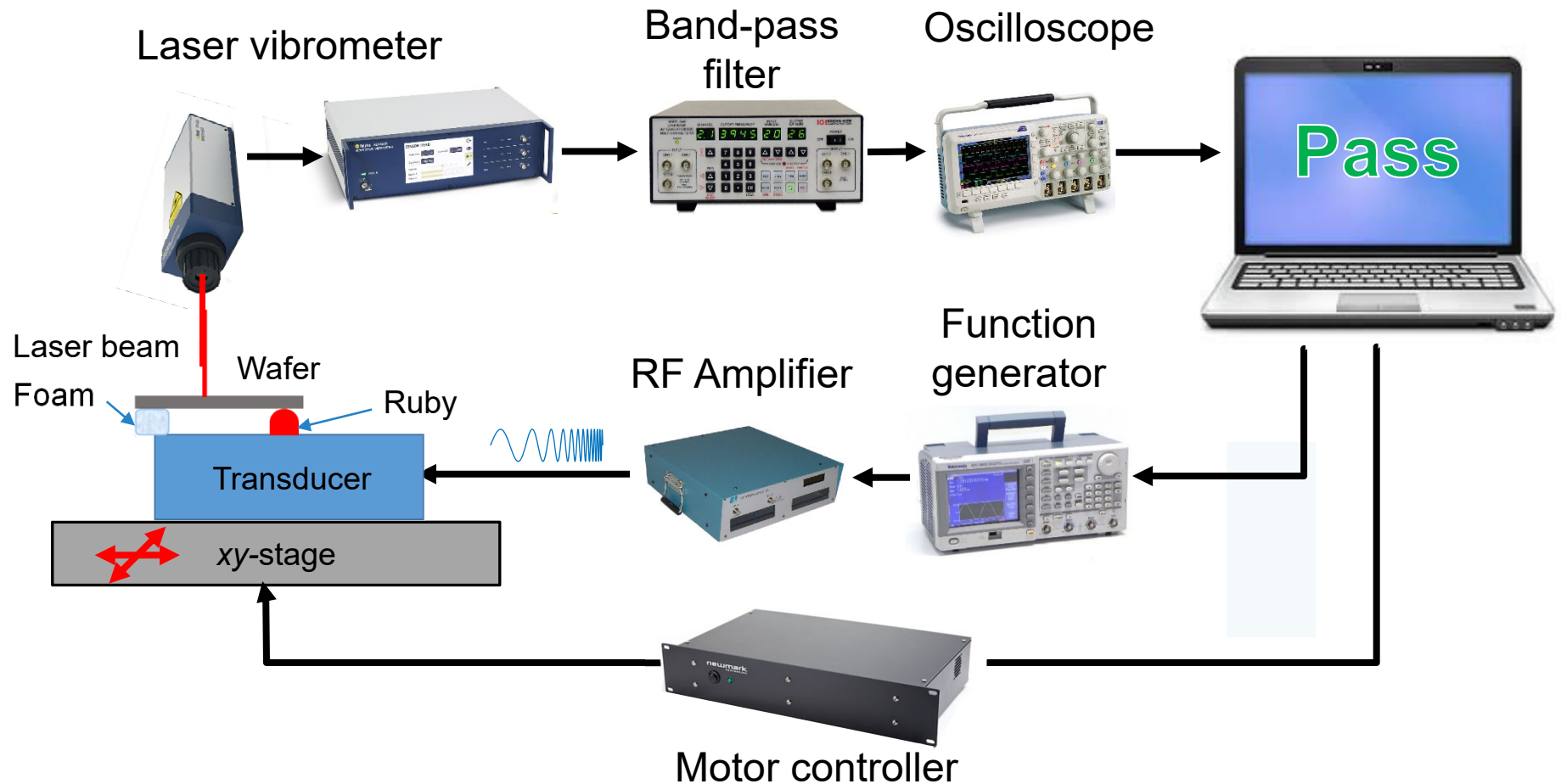


We measure a multi-point scanning pattern across the wafer surface

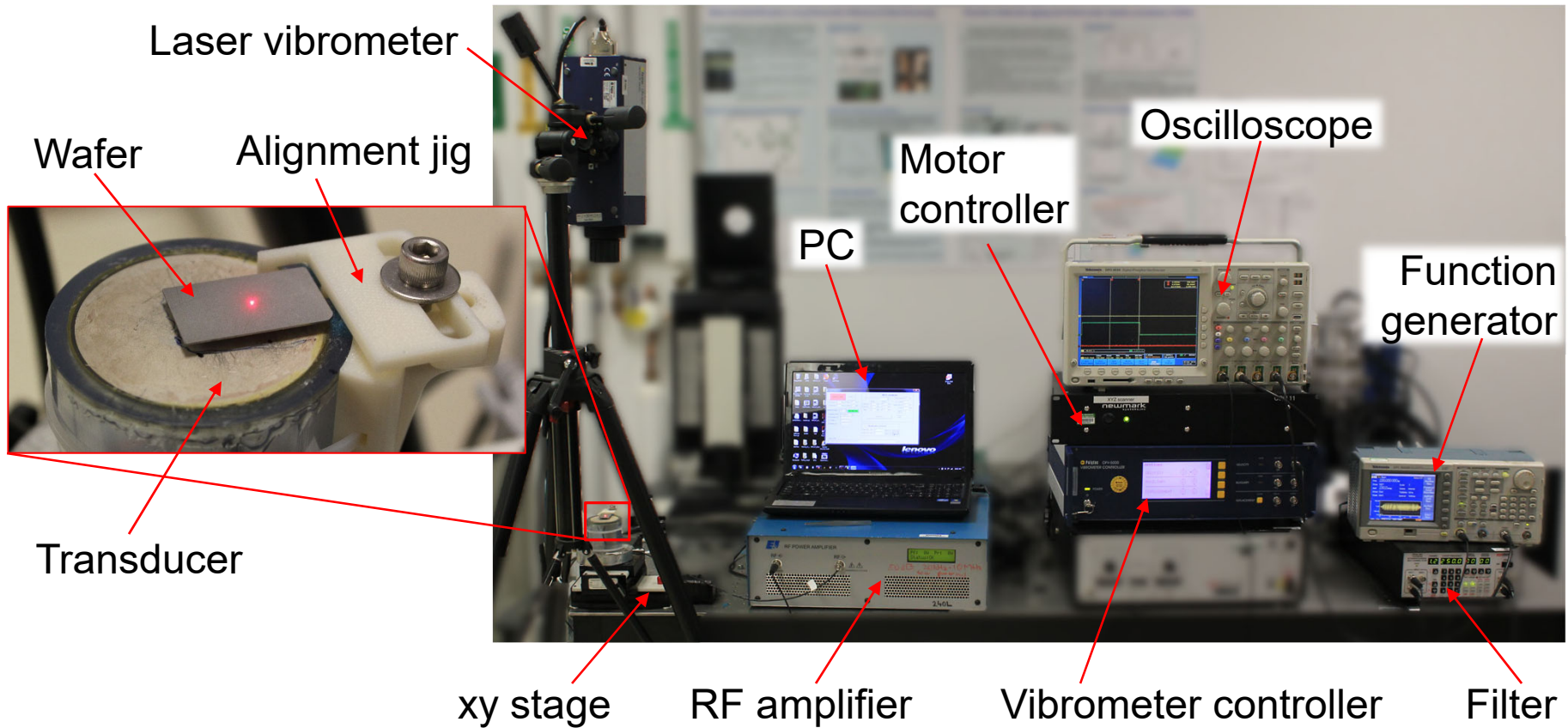


Experimental Setup

Measurement process controlled via a single PC



Experimental Setup (2)

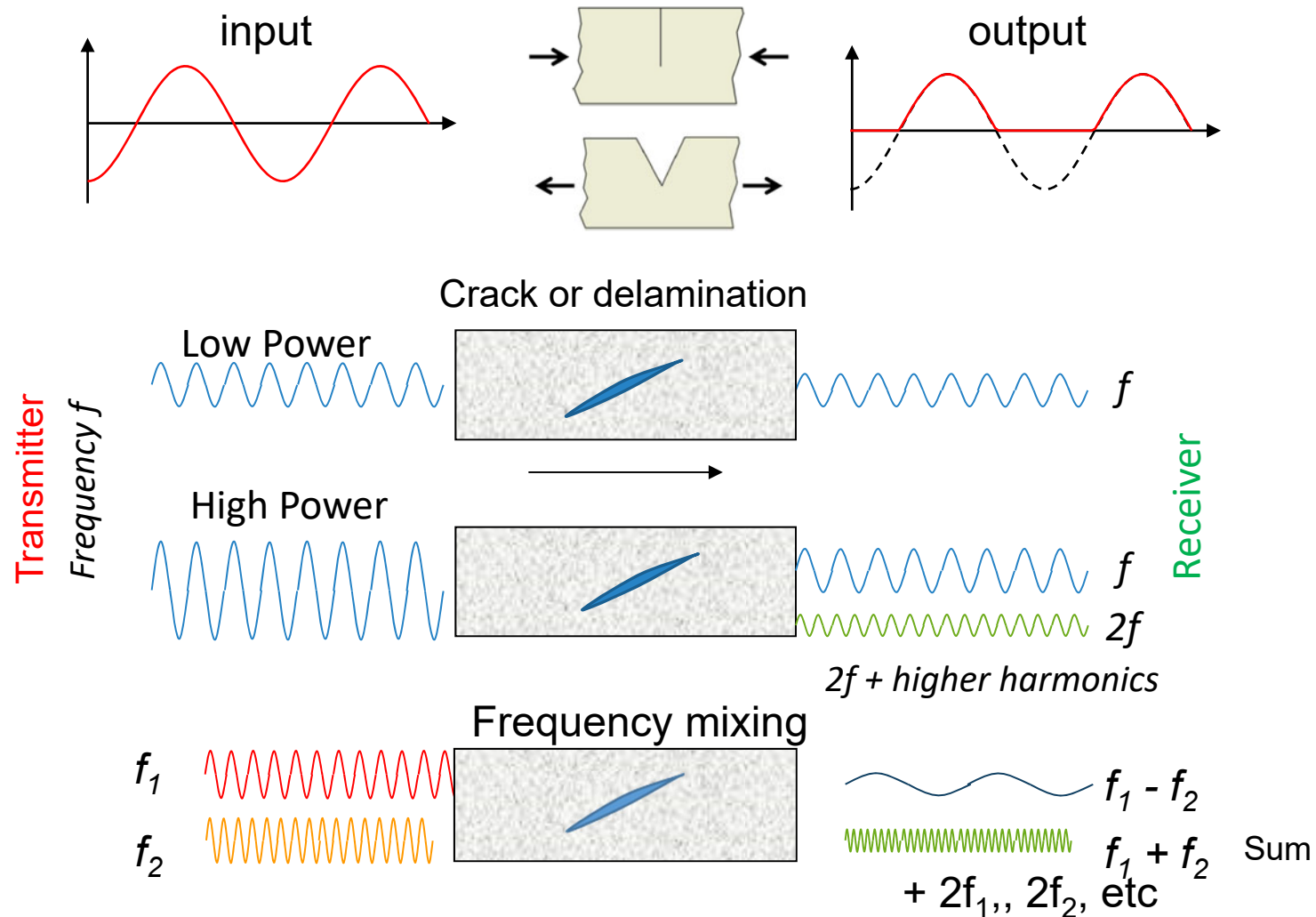


Damage detection metrics

- Acoustic nonlinearity: harmonics
- Acoustic nonlinearity: modulation
- Resonance mode consistency
- Resonance mode amplitude

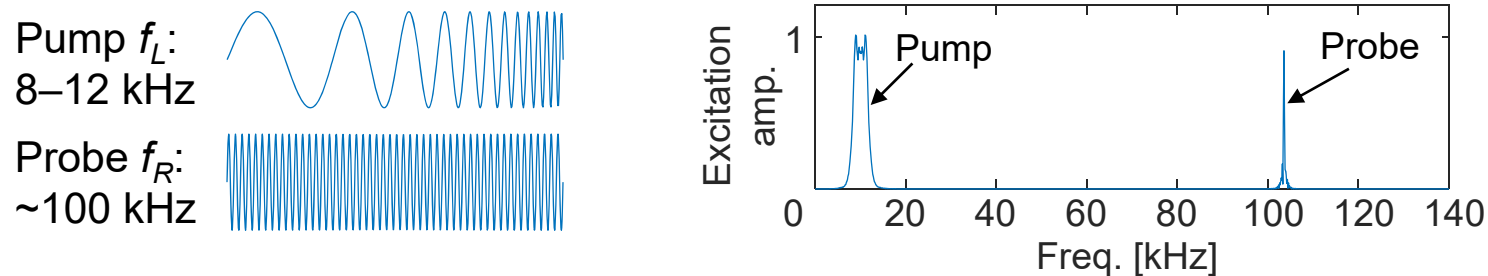
Acoustic Nonlinearity

Contact acoustic nonlinearity: Cracks open/close resulting in nonlinearities

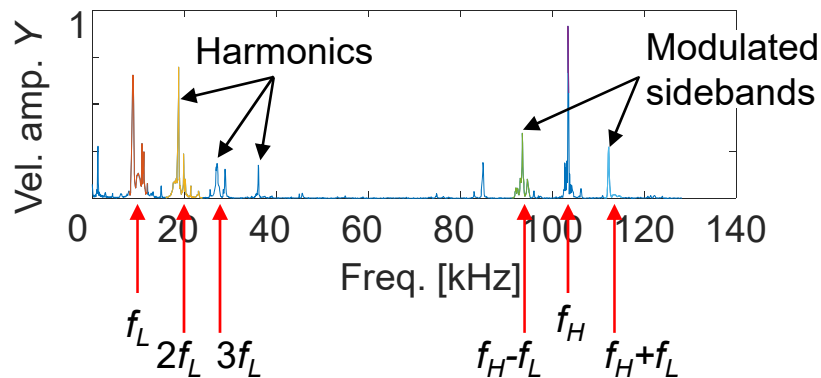


Acoustic Nonlinearity (2)

We input a low-frequency, sweeping “Pump” signal and high-frequency, fixed “Probe” signal



This will result in nonlinear harmonics and modulated sidebands



Nonlinearity metrics:

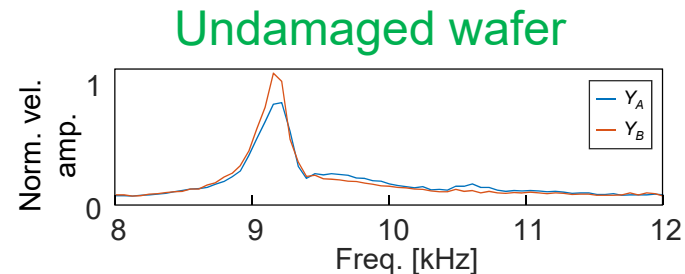
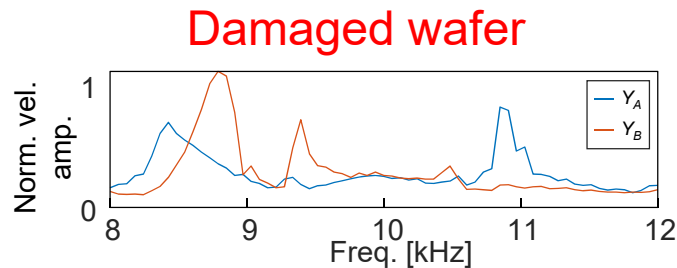
$$\text{Harmonics: } M_{harm} = \frac{\|Y_{2L} + Y_{3L}\|}{\|Y_L\|}$$

$$\text{Modulated sidebands: } M_{mod} = \frac{\|Y_{H+L} + Y_{H-L}\|}{\max Y}$$

Response consistency

Frequency response of undamaged wafers is less sensitive to the location of the excitation/supports

We excite both sides (A, B) of the wafer, and compare the responses



A/B consistency is quantified as

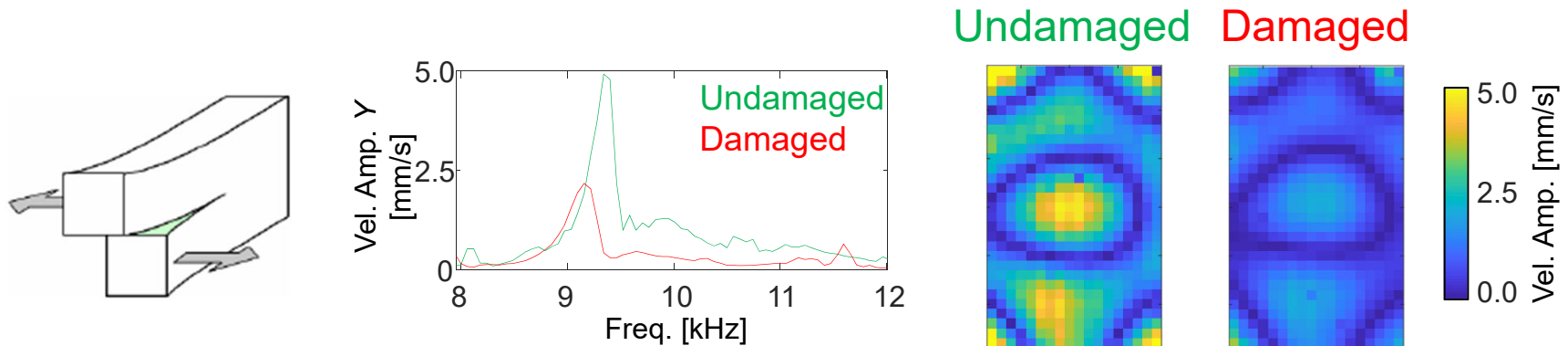
$$\text{A/B consistency: } M_{con} = \frac{\langle Y_A, Y_B \rangle}{|Y_A|_1 |Y_B|_1}$$

High A/B consistency implies an undamaged wafer

Low A/B consistency implies a damaged wafer

Mean amplitude

Friction between crack faces absorbs energy and reduces the resonance amplitude



Mean resonance amplitude is quantified as

$$\text{Mean amplitude: } M_{amp} = \frac{1}{N} \sum_{i=1}^N Y_i$$

High mean amplitude implies an **undamaged wafer**

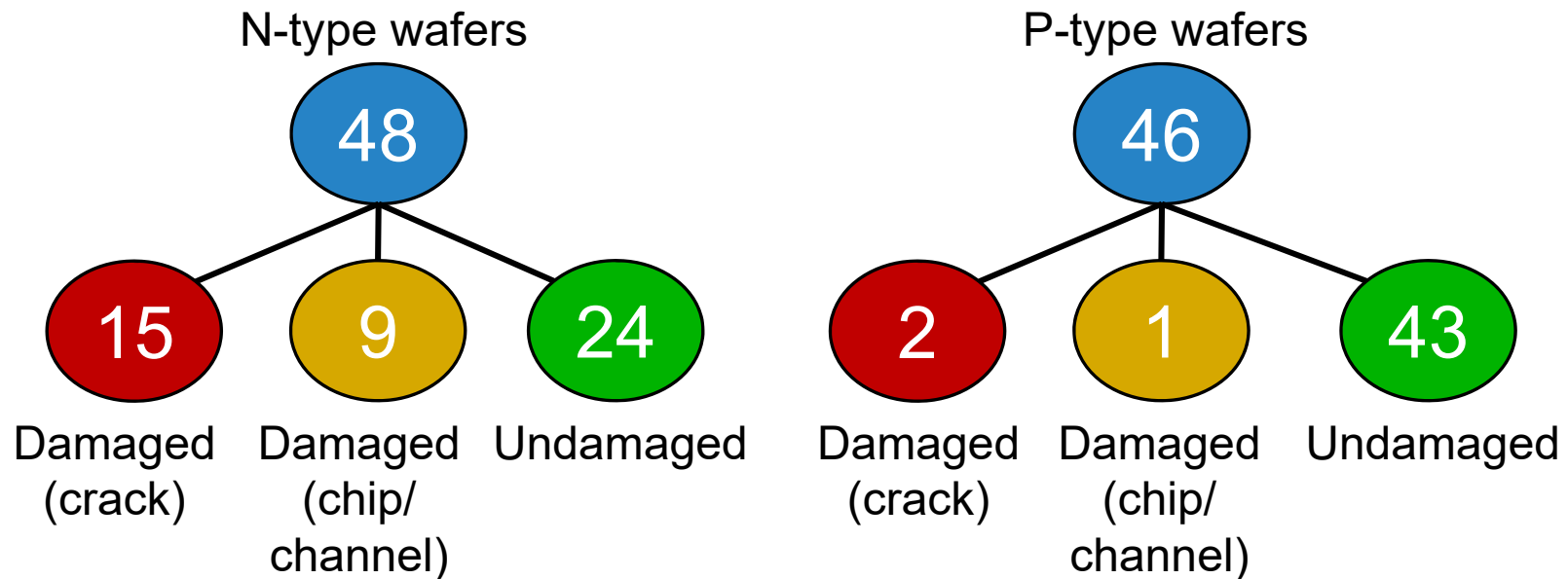
Low mean amplitude implies a **damaged wafer**

Statistical trial of wafers (Optical measurement)



Keyence VHX 6000

- We characterize wafers defects optically
- Wafers with defect depths $>110\text{ }\mu\text{m}$ are characterized as “**damaged**” and defect depths $<110\text{ }\mu\text{m}$ are characterized as “**undamaged**”



Statistical trial of wafers (Acoustic measurement)

Acoustic damage classification using:

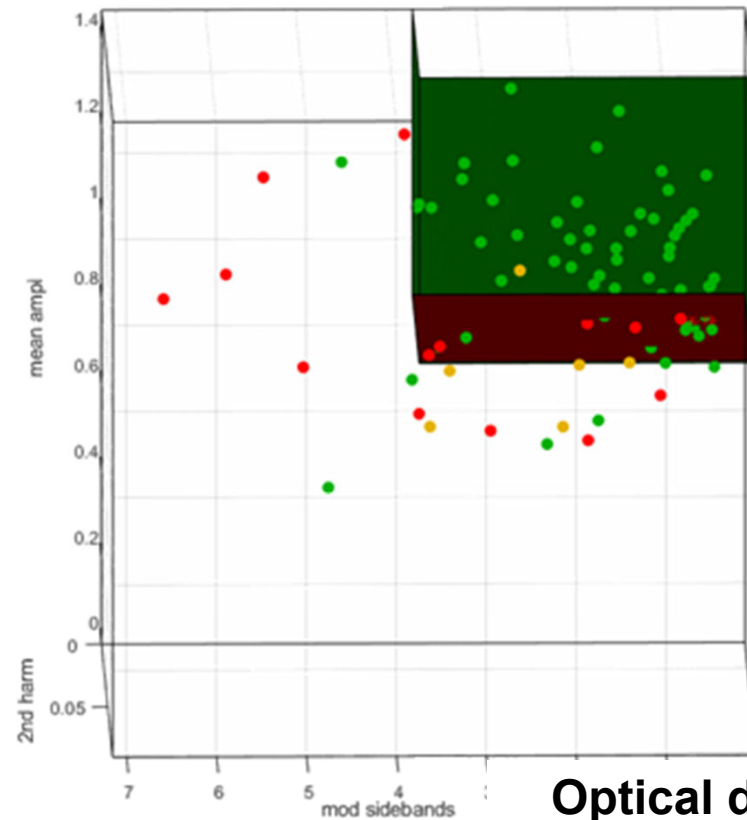
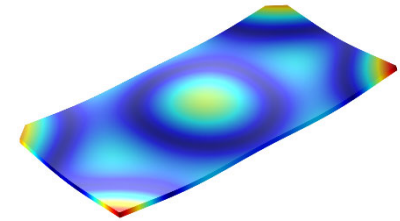
- 2nd harmonic
- Modulated sidebands
- Mean amplitude

Inside box: undamaged

Outside box: damaged

Observations:

- 17/17 cracked wafers FAIL
- 6/10 chip/channel wafers FAIL
- 56/67 undamaged wafers PASS



Optical damage

- Damage < 110 μm
- Chip/channel > 110 μm
- Crack > 110 μm

Statistical trial of wafers (Acoustic measurement)

Acoustic damage classification using:

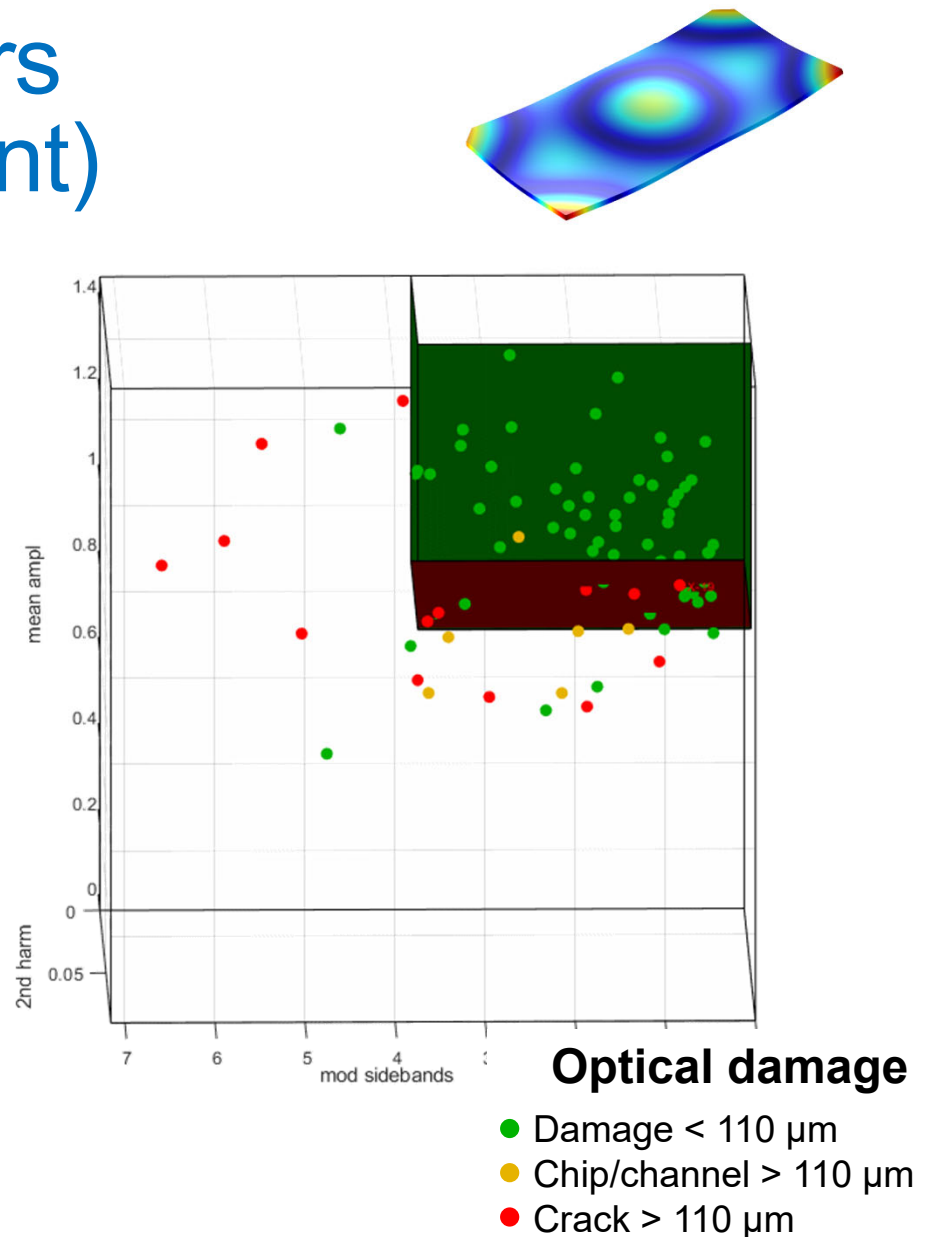
- 2nd harmonic
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Inside box: undamaged

Outside box: damaged

Observations:

- 17/17 cracked wafers FAIL
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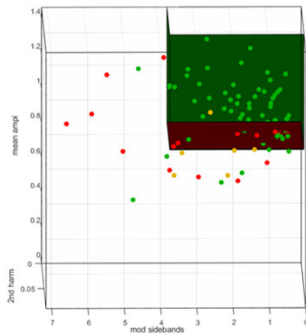
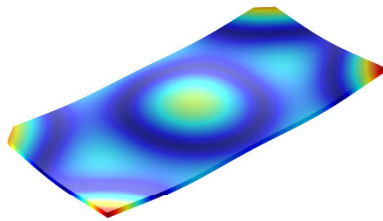
Comparison of damage measurement techniques

We characterize defects using three measurement techniques:

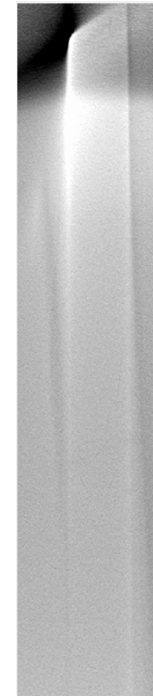
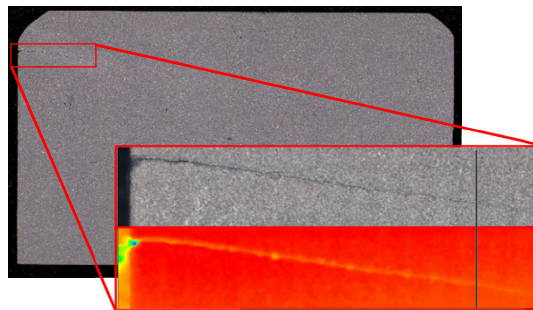
1) Acoustic resonance

2) Optical microscopy

3) X-ray computed tomography

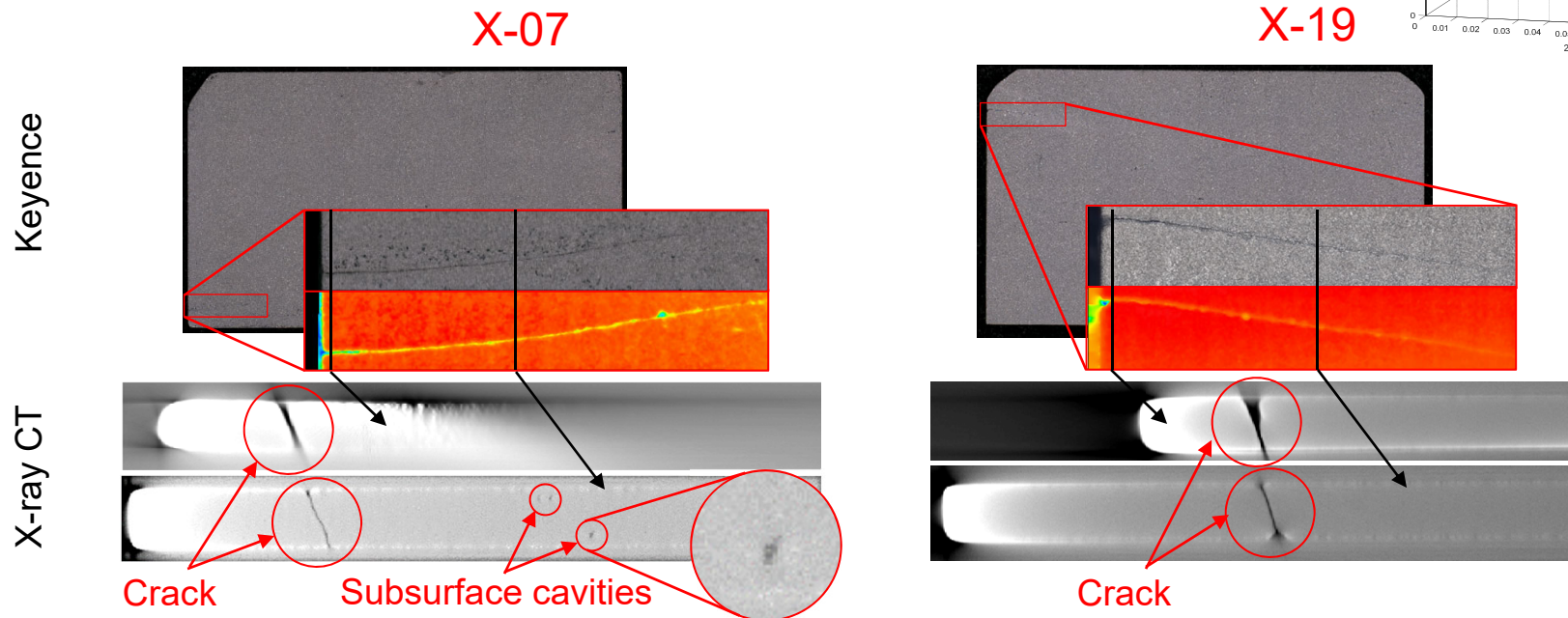
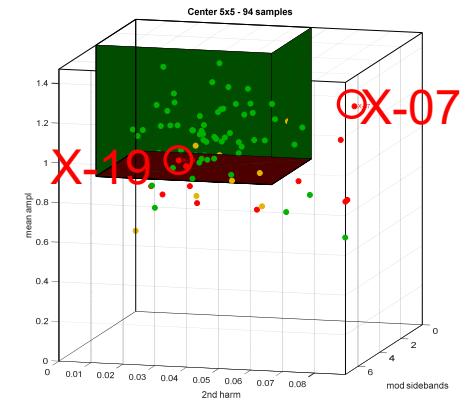


Keyence VHX
6000



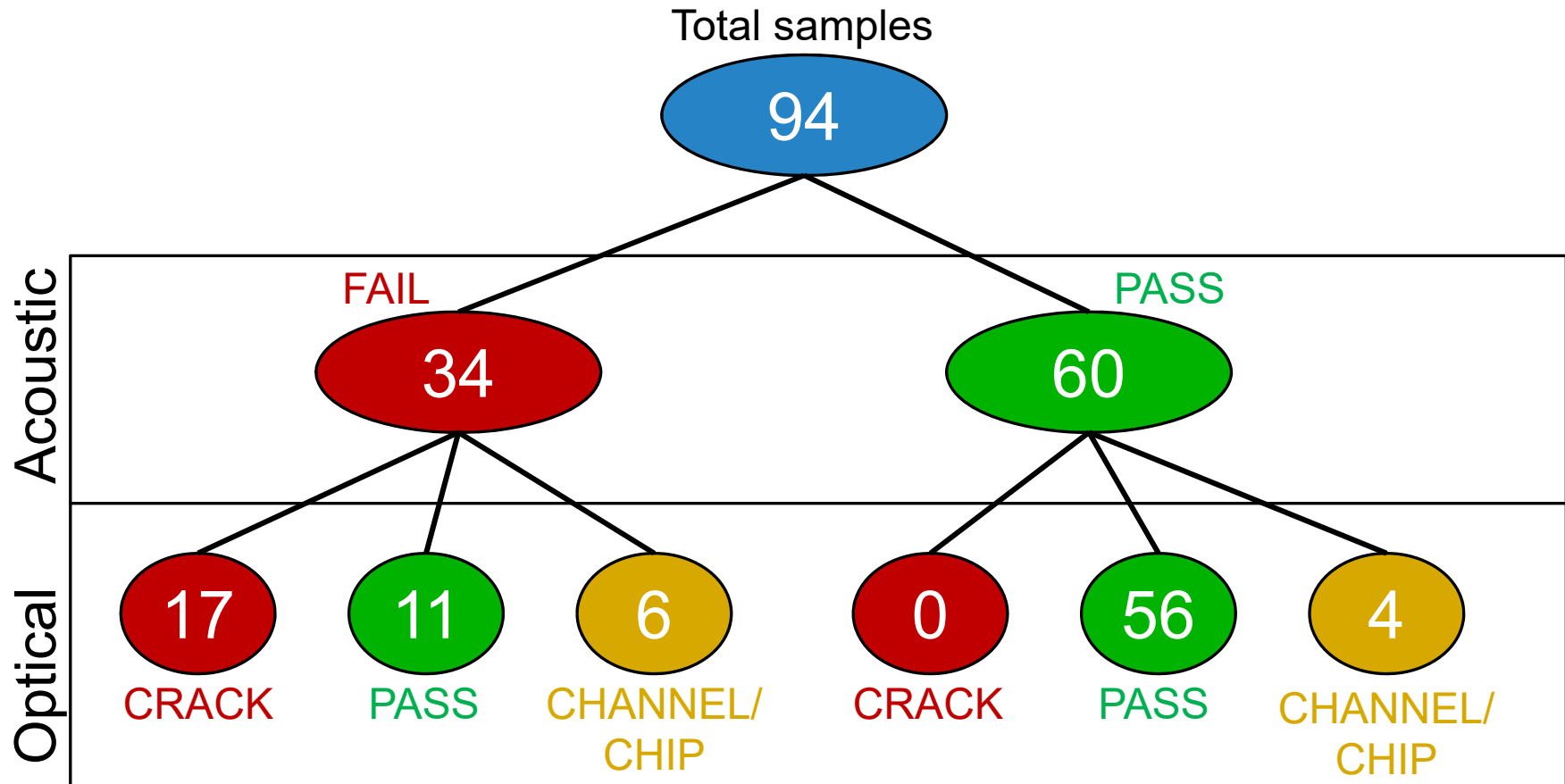
Comparison of damage measurement techniques (2)

Why do some cracks result in higher nonlinear acoustic effects?
E.g. X-07 shows high-amp nonlinear features, but
X-19 shows low-amp nonlinear features



- X-19 cracks are wider and inhibit crack “breathing,” which inhibits acoustic nonlinearities
- Additionally, we observe subsurface cavities in X-07, which implies that there can be defects that are not observable optically
 - Thus, some false positives may contain subsurface defects

Bottom line

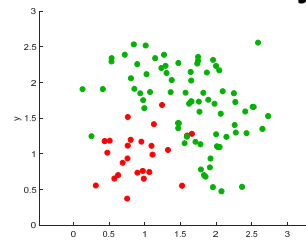


- We correctly classify cracks with 0.0 % total error
- We correctly classify channels/chips with 4.3 % total error
- We correctly classify undamaged wafers with 11.7 % total error

Machine learning damage classification: adaBoost

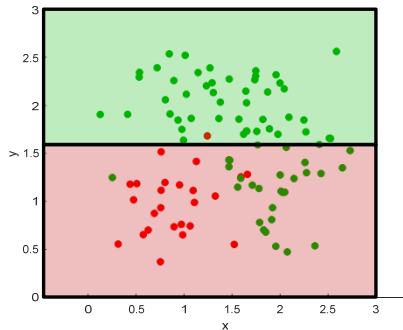
Creates a strong classifier to identify damaged/undamaged wafers by combining multiple weak classifiers

Example: Two damage metrics x and y

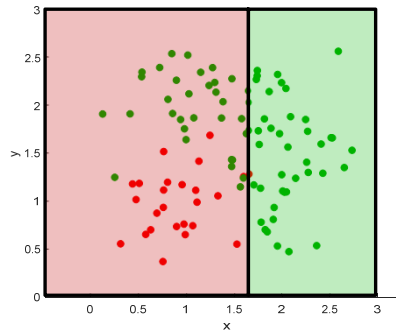


Undamaged wafer
Damaged wafer

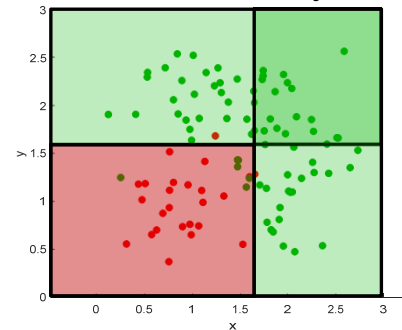
Weak classifier 1
70 % accuracy



Weak classifier 2
66 % accuracy



Combined classifier
94 % accuracy



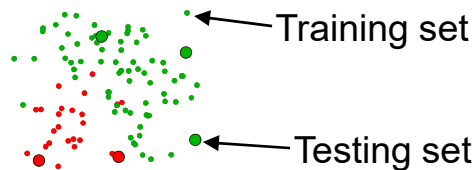
Result: Combining multiple low-accuracy thresholds yields high-accuracy classification

We can add weights to reduce false positives, while increasing false negatives

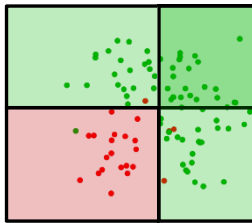
Machine learning damage classification: Experimental results

Machine learning cross-validation

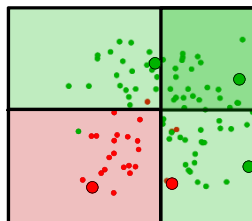
- 1) Randomly separate samples into a “training set” and a “testing set”



- 2) Train the classifier using the “training set”

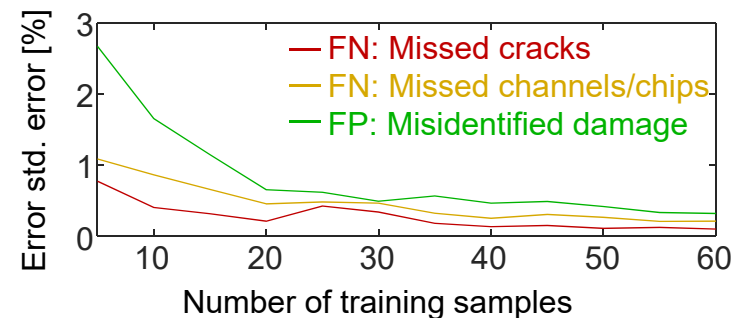
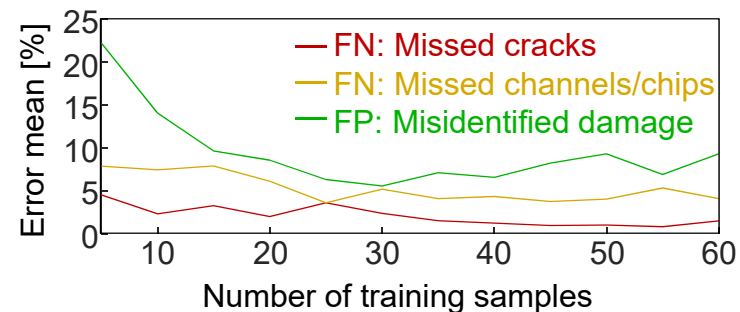


- 3) Test the classifier using the “training set” and “test set”



adaBoost using 7 metrics

- Acoustic nonlinearity: harmonics for sides A & B
- Acoustic nonlinearity: modulation for sides A & B
- Resonance mode amplitude for sides A & B
- Resonance mode consistency



*Cross-validation using 20 tests, each with a test set of 30 data points

Summary

Accomplished goal: Demonstrated acoustic detection of all cracks and most chips/channels

Fast measurement time (<3 mins per wafer)

Combined acoustic/optical measurements enables classification of “damaged” wafers based on acoustic response

High measurement accuracy

- 0.0 % missed cracks
- 4.3 % missed channels/chips (1 channel, 3 chips)
- 11.7 % “misidentified” damage

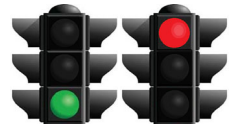
Increased accuracy and confidence with additional training samples

Machine learning enables high-accuracy/reliability and adaptability (with large data sets)

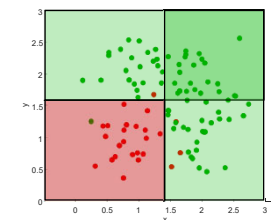
WTF

(What's the Future?)

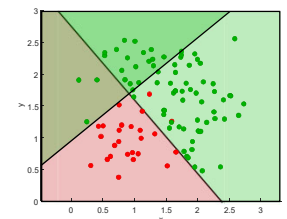
- Package device: Indus Instruments, Houston TX
- Improve wafer jig for increased loading speed and consistency
- Automate optical crack detection via computer vision
- Improve machine learning algorithm by, e.g. changing from 1D weak classifiers to hyper-plane weak classifiers
- Increase machine learning training set size to increase accuracy and confidence
 - Online learning: new wafers are included in the data set during production
 - Batch learning: provide us with a production batch of wafers to include ahead of production (~1 month per 100 wafers)



1D
weak classifiers



Hyper-plane
weak classifiers



Funding

Carry-over from FY18 \$250K

- Improved, user-friendly wafer loading jig
- Improved COTS acoustic source (Olympus V1011)
- Integrate data analysis in the acquisition software

Outstanding needs for FY19 \$265K

- Inspection System Development (INDUS + SSS) – Green light/Red light
 - ~6 months to delivery (from time when funds in hand)

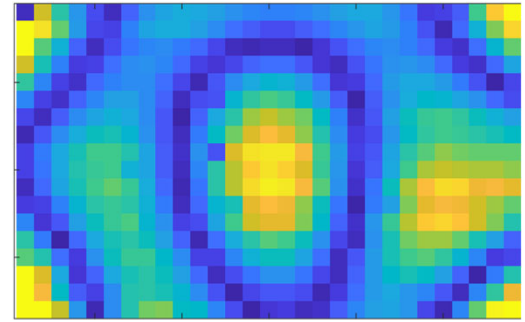
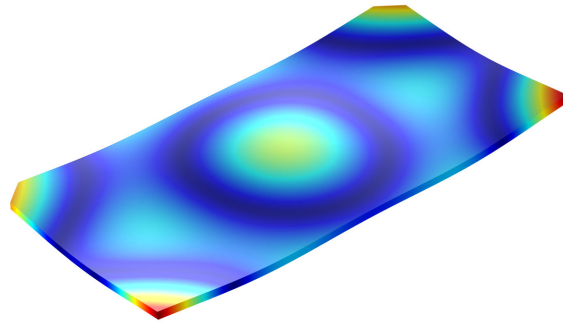
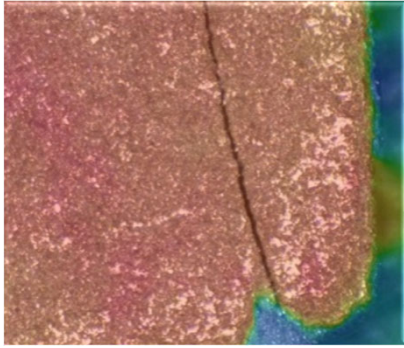
Recommended actions

- | | |
|--|--------|
| • Improved statistics, 100 more samples in the lab | \$50K |
| • Automated optical crack detection | \$200K |
| • Improved machine learning algorithm | \$200K |

Additional system

- | | |
|------------------------------|--------|
| • Equipment cost (Acoustics) | \$170K |
| • Equipment cost (Optics) | \$85K |
| • Packaging (INDUS) | \$25K |

*Originally 1 - KCP, 1 – spare KCP, 1 - LANL



Thank you

